IOT BASED SYSTEM FOR PARALYZED HAND CONTROL

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Dissertation submitted in partial fulfillment of the requirements for the
Bachelor of Science (Hons) in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology
Sri Lanka

April 2026

MEASURE AND MONITOR PARALYSIS IMPROVEMENT USING A PRESSURE BALL

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DECLARATION

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Abstract

Stroke-induced paralysis causes significant loss of hand motor function, making grip strength recovery a critical biomarker in rehabilitation assessment. Conventional dynamometers provide only a single aggregate force reading during periodic clinical visits, failing to capture spatial force distribution and limiting monitoring to weekly intervals. This dissertation presents the design, implementation, and validation of an Internet of Things enabled pressure ball device embedded with six Force-Sensitive Resistor (FSR402) sensors for continuous measurement and monitoring of paralysis improvement in stroke rehabilitation patients. The pressure ball serves as a dual-purpose therapeutic and assessment tool: patients squeeze it during therapy sessions while the distributed sensor array simultaneously captures individual force contributions from the thumb, index, middle, ring, and little fingers, and from the palm region, enabling detection of compensatory gripping patterns that single-point measurements cannot reveal.

A novel hybrid calibration methodology addresses the fundamental scale discrepancy between multi-sensor pressure ball readings and standard single-sensor dynamometer values. The methodology computes two complementary metrics: total grip strength, representing raw sensor summation for tracking individual patient progress over time, and equivalent grip strength, derived using an empirically determined calibration factor of 1.28 for direct comparison against published clinical normative values. The calibration factor was established through a cross-instrument comparison study with 15 healthy participants, yielding a coefficient of variation of 1.2%, confirming that a single universal factor is sufficient without per-patient calibration. An ESP32 microcontroller acquires sensor data through dual ADS1115 16-bit analog-to-digital converters and transmits measurements to a Flask-based cloud server deployed on AWS EC2. A TensorFlow neural network classifies patients into five recovery stages with 95.2% accuracy using the calibrated equivalent grip metric. A role-based web dashboard provides real-time monitoring for patients, doctors, and administrators. System testing confirms per-sensor accuracy within ±0.2 kg, a repeatability coefficient of variation of 3.2%, sub-100 millisecond transmission latency, and clinically valid recovery assessments consistent with standard dynamometer evaluations.

Keywords: Pressure ball, paralysis monitoring, grip strength, IoT healthcare, Force-Sensitive Resistors, stroke rehabilitation, hybrid calibration, machine learning

ACKNOWLEDGEMENT

The successful completion of this individual research component would not have been possible without the guidance, support, and encouragement of several individuals, to whom I extend my sincere gratitude.

First and foremost, I would like to express my deepest appreciation to my supervisor, Miss Narmada Gamage of the Department of Information Technology, Sri Lanka Institute of Information Technology (SLIIT), for her invaluable guidance, constructive feedback, and continuous encouragement throughout this research. Her insights and direction during supervision meetings played a crucial role in shaping both the technical depth and academic rigour of this study.

I would also like to extend my gratitude to my project team members for their collaboration, technical discussions, and collective efforts in developing the broader IoT-based system for paralyzed hand control. Their contributions across multiple modules created a supportive and intellectually stimulating environment that greatly contributed to the success of this individual pressure ball monitoring component.

Special acknowledgement is given to the fifteen volunteer participants who generously contributed their time for the calibration study and device usability testing. Their patience during repeated measurement trials and candid feedback on device ergonomics were instrumental in validating the hybrid calibration methodology.

Finally, I am sincerely grateful to my family for their financial support, unwavering patience, and constant encouragement throughout my undergraduate studies.

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LIST OF ABBREVIATIONS

Abbreviation	Description
ADC	Analog-to-Digital Converter
API	Application Programming Interface
ASHT	American Society of Hand Therapists
AWS	Amazon Web Services
CORS	Cross-Origin Resource Sharing
EC2	Elastic Compute Cloud
ESP32	Espressif Systems 32-bit Microcontroller
FSR	Force-Sensitive Resistor
HTTP	HyperText Transfer Protocol
I2C	Inter-Integrated Circuit
IoT	Internet of Things
JSON	JavaScript Object Notation
JWT	JSON Web Token
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
REST	Representational State Transfer
SLIIT	Sri Lanka Institute of Information Technology
SQL	Structured Query Language
TLS	Transport Layer Security
WHO	World Health Organization

1. INTRODUCTION

1.1 Background and Literature Survey

Stroke is among the most significant causes of acquired long-term disability worldwide. The World Health Organization reports that approximately 15 million people experience stroke annually, of whom 5 million are left with permanent disability [1]. Among stroke survivors, nearly 80 percent experience some degree of upper limb motor impairment, and hand function deficits are consistently identified as among the most functionally debilitating consequences. The ability to grasp, squeeze, hold, and manipulate objects underpins virtually all activities of daily living, from feeding and dressing to writing and tool operation. Loss of grip strength through paralysis fundamentally reduces independence and quality of life, imposing substantial burden on patients, caregivers, and healthcare systems.

Paralysis, defined as partial or complete loss of voluntary muscle function following neurological injury, manifests on a wide severity spectrum in stroke patients [2]. Hand paralysis may range from complete flaccidity where no voluntary grip force can be generated, through varying degrees of paresis where reduced force capacity limits functional task performance, to near-complete recovery where residual weakness is detectable only by sensitive quantitative instruments. The trajectory of recovery varies considerably between individuals and is influenced by stroke severity, lesion location, patient age, pre-morbid health status, and the intensity and duration of rehabilitation [3].

Monitoring this recovery trajectory through objective, quantitative measurement is fundamental to evidence-based rehabilitation practice. Accurate longitudinal grip strength data enables clinicians to adjust treatment intensity, predict functional outcomes, detect recovery plateaus requiring intervention modification, evaluate therapeutic approaches, and communicate progress to patients and families. Traditional rehabilitation assessment relies on periodic clinical visits, typically at weekly or biweekly intervals. This sparse temporal resolution creates gaps in the recovery data record and may miss day-to-day fluctuations, dose-response relationships, and subtle improvement trends that could guide therapeutic optimisation [3].

Rehabilitation therapy for the paralysed hand typically involves repetitive gripping exercises using squeeze balls, therapy putty, spring-loaded exercisers, and cylindrical grasp trainers. These tools provide graded resistance against which patients perform repeated contractions to stimulate neuromuscular recovery through activity-dependent neuroplasticity [2]. However, conventional therapy tools lack integrated measurement capability, requiring entirely separate assessment sessions using dedicated dynamometer instruments. This procedural separation between therapeutic activity and quantitative measurement creates barriers to frequent monitoring, limits longitudinal data for evidence-based planning, and eliminates the opportunity for immediate performance feedback during home exercise programs.

Conventional handheld dynamometers, particularly the Jamar hydraulic instrument endorsed by the American Society of Hand Therapists (ASHT) as the clinical gold standard, measure the maximum isometric grip force through a single strain gauge assembly [4]. The ASHT standardised protocol specifies patient positioning (seated, shoulder adducted, elbow at 90 degrees, forearm neutral), handle position (second position for standardisation), and measurement procedure (three maximum effort trials with 60-second rest intervals). This standardisation has enabled the accumulation of extensive age- and gender-stratified normative databases, as summarised in Table 1.1.

Table 1.1: Grip strength normative values by age and gender [5]

Age Group	Male Mean (kg)	Male SD	Female Mean (kg)	Female SD
20–24	48.5	8.2	30.1	5.4
25–29	49.2	8.5	31.0	5.8
30–34	49.0	8.0	30.8	5.6
35–39	47.8	7.9	29.5	5.5
40–44	46.5	8.1	28.3	5.3
45–49	44.2	7.8	27.0	5.2
50–54	42.0	7.5	25.8	5.0
55–59	40.3	7.6	24.5	4.8
60–64	38.0	7.2	23.2	4.7
65–69	35.5	7.0	21.5	4.5
70+	32.0	6.8	19.8	4.3

Despite their established clinical utility, conventional dynamometers exhibit fundamental limitations in continuous paralysis monitoring contexts. First, they provide only a single aggregate force value and cannot differentiate contributions from individual fingers, the thumb, and the palm. This prevents detection of compensatory gripping strategies where patients unconsciously redistribute force through stronger muscles while neurologically affected intrinsic finger muscles remain weak. Kim et al. [6] demonstrated that such compensation patterns are prevalent in stroke recovery and can mask incomplete neurological deficit from clinicians relying solely on aggregate force measurements. A patient generating apparently adequate total force through thumb and palm compensation while index and ring finger intrinsic muscles remain paralysed may appear functionally recovered by dynamometer assessment despite clinically significant underlying deficit.

Second, dynamometer assessment requires dedicated clinical sessions with trained personnel, limiting frequency to weekly or biweekly intervals. Third, the rigid metallic form factor differs substantially from therapeutic objects patients use during exercises, potentially affecting grip posture and measurement ecological validity. Fourth, conventional dynamometers lack wireless connectivity, cloud storage, automated trend analysis, and visualisation capabilities, requiring manual documentation in clinical notes and making longitudinal data analysis laborious.

The Internet of Things (IoT) paradigm offers transformative potential for continuous rehabilitation monitoring. By embedding sensor technology directly into therapeutic exercise devices and connecting them to cloud analytics platforms, IoT systems can achieve unprecedented temporal resolution in grip strength data collection while providing remote monitoring capabilities that extend beyond the rehabilitation facility into patients' home environments [7]. The ESP32 microcontroller from Espressif Systems has emerged as a leading platform for IoT health monitoring applications due to its integrated dual-band WiFi and Bluetooth connectivity, dual-core Xtensa LX6 processor running at 240 MHz, extensive peripheral interfaces, and competitive pricing suitable for affordable healthcare applications [12].

Force-Sensitive Resistors (FSRs) operate on the piezoresistive principle, wherein applied mechanical force modulates electrical resistance through deformation of a conductive polymer composite deposited on a flexible substrate [8]. The FSR402 model from Interlink Electronics offers a 12.7 mm diameter active sensing area, 0.46 mm profile suitable for embedding within a therapeutic device, and a response time under 5 milliseconds. Paredes-Madrid et al. [9] demonstrated that FSR repeatability can be improved from approximately

15% to approximately 5% coefficient of variation through multi-point calibration curves and pre-conditioning protocols.

Machine learning approaches have demonstrated significant potential for automated recovery stage classification from grip force data combined with demographic and temporal context [10]. Deep neural networks trained on clinical normative distributions can model the complex nonlinear relationships between measured parameters and rehabilitation outcomes, providing real-time objective staging that supplements clinical judgment. However, the accuracy of such models critically depends on receiving inputs on a measurement scale consistent with the normative data used during training.

1.2 Research Gap

A systematic review of published literature at the intersection of instrumented therapeutic devices, multi-sensor grip assessment, and IoT rehabilitation monitoring reveals four specific gaps that this dissertation directly addresses.

Gap 1 – Absence of Therapy-Integrated Measurement: No published work presents an instrumented pressure ball device designed specifically for continuous paralysis monitoring that simultaneously serves as both a therapeutic exercise tool and a quantitative assessment instrument. Existing IoT grip monitoring systems use rigid bar or handle form factors that differ fundamentally from the deformable squeeze objects used in therapy, limiting ecological validity and failing to capture measurements during natural therapy interactions.

Gap 2 – Unresolved Multi-Sensor Calibration: Existing multi-sensor grip systems address sensor-level calibration (converting electrical signals to force units) but neglect system-level calibration — the transformation from distributed multi-point force totals to clinically comparable single-sensor equivalent values. This gap prevents multi-sensor systems from leveraging decades of published normative data derived from single-sensor dynamometers, rendering clinical interpretation unreliable.

Gap 3 – No Dual-Metric Framework: No published system provides a dual-metric approach that simultaneously preserves raw sensor summation for internally consistent longitudinal patient tracking and generates calibrated equivalent values for cross-population clinical comparison. Both metrics are required for comprehensive paralysis monitoring: raw totals for relative improvement tracking and calibrated values for absolute clinical assessment.

Gap 4 – Unvalidated ML Inputs: Machine learning recovery classification models have not been validated with system-level calibrated inputs from multi-sensor therapeutic devices. Using raw uncalibrated multi-sensor totals as inputs to models trained on single-sensor normative data introduces systematic scale bias that degrades classification accuracy.

Table 1.2: Research gap summary

Gap	Prior Art Limitation	This Dissertation's Contribution
Therapy integration	Separate therapy and measurement tools	Dual-purpose pressure ball: therapy + real-time measurement
System-level calibration	Sensor-level calibration only	Hybrid factor 1.28 bridging multi-sensor to clinical scale
Dual metric	Single metric reported	Total grip (longitudinal) + equivalent grip (clinical)
ML input validity	Uncalibrated inputs to clinical-trained models	Calibrated equivalent grip as ML input, 95.2% accuracy

Table 1.3 presents a systematic comparison of the proposed pressure ball system against representative existing approaches across twelve evaluation dimensions. The comparison confirms that while existing systems address individual aspects of grip monitoring, no published solution combines the therapeutic form factor, six-sensor spatial distribution, hybrid system-level calibration, dual-metric framework, machine learning classification with calibrated inputs, and comprehensive role-based IoT dashboard within a single integrated system.

Table 1.3: Comparison of existing grip monitoring systems

Feature	Jamar Dynamometer	Smart Glove [11]	IoT Grip Bar [12]	Proposed (This Work)
Form factor	Rigid handle	Wearable glove	Rigid cylinder	Compliant squeeze ball
Sensor count	1 (strain gauge)	Multiple flex sensors	4 FSR	6 FSR (anatomic)
Force distribution	No	Partial	Limited	Full (6 regions)
Wireless	No	Bluetooth	WiFi	WiFi (ESP32)
System-level calibration	Factory only	No	No	Hybrid factor 1.28

Feature	Jamar Dynamometer	Smart Glove [11]	IoT Grip Bar [12]	Proposed (This Work)
Dual metric	N/A	No	No	Total + Equivalent
Clinical norm valid	Native	Not validated	Not validated	Via calibration
ML classification	No	No	Threshold only	5-stage NN (95.2%)
Role-based dashboard	No	No	Basic display	Patient/Doctor/Admin
Therapy integration	No	Limited	No	Yes – dual-purpose
Estimated unit cost	USD 200–500	USD 150–300	USD 80–120	USD ~65

1.3 Research Problem

The central research problem addressed by this dissertation is: How can an instrumented pressure ball with embedded Force-Sensitive Resistor sensors accurately measure and continuously monitor paralysis improvement in stroke rehabilitation patients, while providing clinically valid measurements comparable to established single-sensor dynamometer standards, enabling detection of compensatory force distribution patterns, and delivering automated recovery stage classification through a cloud-connected IoT platform?

This overarching problem encompasses four interconnected sub-problems: (a) quantifying and correcting the measurement scale discrepancy between multi-sensor pressure ball readings and single-sensor dynamometer values through a principled hybrid calibration methodology; (b) validating the corrected measurements against clinical normative data for accurate recovery percentage calculation; (c) integrating machine learning classification that receives appropriately calibrated inputs for reliable automated recovery staging; and (d) implementing a complete IoT system enabling remote paralysis monitoring through an accessible, role-based web dashboard for patients, clinicians, and administrators.

1.4 Research Objectives

This dissertation aims to achieve the following specific objectives:

1. Design and fabricate a pressure ball device embedded with six FSR402 force sensors positioned at anatomically relevant hand regions — thumb, index, middle,

ring, pinky, and palm — interfaced with an ESP32 microcontroller through dual ADS1115 16-bit analog-to-digital converters for multi-channel force data acquisition.

2. Develop a hybrid calibration algorithm that computes both total grip strength (raw sensor summation for consistent longitudinal patient tracking) and equivalent grip strength (calibrated measurement comparable to Jamar dynamometer normative values) with empirical determination of the calibration factor through a controlled cross-instrument comparison study with healthy participants.
3. Implement a Flask-based cloud backend server with RESTful API design, SQLite database supporting dual-metric storage, JSON Web Token authentication with role-based access control, session management, and recovery percentage calculation using calibrated equivalent grip against age- and gender-adjusted normative values.
4. Integrate a TensorFlow neural network for automated five-stage paralysis recovery classification — Severe Paralysis, Poor Recovery, Fair Recovery, Good Recovery, Excellent Recovery — using the calibrated equivalent grip metric to provide immediate post-session feedback on recovery status.
5. Develop a role-based web dashboard enabling patients to visualise their paralysis improvement trajectory through live six-sensor readings and historical progress charts, doctors to monitor patient recovery and set treatment baselines, and administrators to manage the system infrastructure including device registration and diagnostic testing.
6. Deploy the complete system on AWS EC2 cloud infrastructure and validate through a 15-participant calibration study, sensor accuracy characterisation, 18 test case execution, performance benchmarking, and clinical comparison testing demonstrating the necessity and effectiveness of the hybrid calibration approach.

2. METHODOLOGY

2.1 System Architecture

The paralysis monitoring system is structured as a three-tier Internet of Things architecture separating the sensing layer (instrumented pressure ball), processing layer (cloud backend), and presentation layer (web dashboard). This decomposition enables independent development and testing of each tier while maintaining well-defined interfaces for inter-layer communication.

At the sensing layer, the pressure ball device acquires grip force data from six FSR402 sensors at 10 Hz through dual ADS1115 16-bit analog-to-digital converter modules communicating via I2C serial protocol. The ESP32 firmware applies a 14-point piecewise linear calibration curve, maintains five-sample moving average filters for noise suppression, computes both total grip strength (S1+S2+S3+S4+S5+S6) and equivalent grip strength (total × 1.28), and transmits the complete measurement as a structured JSON payload to the cloud server via HTTP POST over WiFi.

At the processing layer, the Flask web application running on AWS EC2 authenticates incoming requests using JSON Web Tokens, identifies the active measurement session associated with the reporting device, retrieves the patient profile (age, gender, baseline grip) from the SQLite database, calculates the recovery percentage by comparing calibrated equivalent grip against age- and gender-matched normative values, classifies the recovery stage using TensorFlow neural network inference, and persists the complete measurement record including all six individual sensor values, both grip metrics, recovery percentage, stage classification, health status label, and ML confidence score.

At the presentation layer, a responsive single-page web application renders role-specific views with Chart.js for data visualisation, polling the backend API at two-second intervals during active measurement sessions to display live sensor readings with animated value transitions.

2.2 Pressure Ball Hardware Design

2.2.1 Physical Construction

The pressure ball was fabricated using a semi-rigid polyurethane foam sphere of 75 mm diameter, selected to accommodate the average adult hand during cylindrical power grip while providing sufficient internal volume for electronics housing. The foam offers controlled compliance that yields under grip pressure to activate the embedded FSR sensors while maintaining structural integrity across thousands of repeated squeeze cycles. The exterior is covered with a medical-grade silicone sleeve providing a comfortable non-slip grip surface, moisture resistance for hygiene compliance, and secure adhesive bonding surfaces for sensor positioning.

Six FSR402 sensors were affixed to the ball surface at predetermined anatomical contact positions using biocompatible adhesive, with each sensor's 12.7 mm active area oriented flush with the ball surface to ensure direct force coupling. Thin 28 AWG silicone-insulated wiring routes each sensor through channels formed in the foam to a central electronics cavity at the core, where the ESP32 microcontroller, ADS1115 modules, and a 3.7 V 500 mAh lithium polymer battery are housed within a 3D-printed PLA enclosure.

2.2.2 Electronic Subsystem

Table 2.1: Hardware component specifications and estimated costs

Component	Model / Specification	Qty	Unit Cost (USD)	Total (USD)
Microcontroller	ESP32-DevKitC V4 (240 MHz)	1	8.00	8.00
ADC module	ADS1115 16-bit I2C	2	3.50	7.00
Force sensor	FSR402 (Interlink Electronics)	6	6.00	36.00
Reference resistor	10 kΩ, ¼W, 1% metal film	6	0.05	0.30
Foam ball	75 mm polyurethane sphere	1	2.00	2.00
Silicone sleeve	Medical-grade moulded	1	3.00	3.00
3D-printed enclosure	PLA internal housing	1	1.50	1.50
Battery	3.7 V 500 mAh LiPo	1	4.00	4.00
Wiring	28 AWG silicone set	1 set	2.00	2.00
USB cable	Micro-USB charging	1	1.50	1.50
Total				**65.30**

2.2.3 Circuit Design

Each FSR402 sensor is connected in a voltage divider configuration with a 10 kΩ precision metal-film resistor (1% tolerance). The FSR connects between the 5 V supply rail and the junction node; the reference resistor connects between the junction and ground. Under zero applied force, FSR resistance exceeds 1 MΩ, producing near-zero junction voltage. As force increases, FSR resistance decreases, raising junction voltage toward 5 V. The ADS1115 analog inputs safely accept up to 6.144 V in the default gain configuration, fully accommodating the 0–5 V output range.

I2C communication uses ESP32 GPIO 21 (SDA) and GPIO 22 (SCL) with 4.7 kΩ pull-up resistors to 3.3 V. ADS1115 module 1 (I2C address 0x48, ADDR pin to GND) acquires channels A0–A3 corresponding to sensors 1–4 (thumb, index, middle, ring). ADS1115 module 2 (address 0x49, ADDR pin to VDD) acquires channels A0–A1 corresponding to sensors 5–6 (pinky, palm), with channels A2–A3 reserved for future expansion.

2.3 Sensor Placement and Signal Conditioning

2.3.1 Anatomical Placement

Table 2.3: Sensor placement with anatomical and clinical mapping

Sensor	Hand Region	Anatomical Landmark	Nerve Supply	Clinical Significance
S1	Thumb	Thenar eminence	Median	Major force contributor; common compensation site
S2	Index finger	Distal phalanx	Median	Precision grip key; early recovery indicator
S3	Middle finger	Distal phalanx	Median	Strongest digit; primary power grip contributor
S4	Ring finger	Distal phalanx	Ulnar	Intrinsic muscle strength assessment
S5	Little finger	Distal phalanx	Ulnar	Ulnar nerve recovery indicator
S6	Palm	Hypothenar	Ulnar	Overall grip stabilisation and force base

This distribution enables nerve-specific recovery pattern detection. Median nerve recovery manifests as increasing force in sensors 1–3; ulnar nerve recovery appears as increasing force in sensors 4–6. A patient demonstrating strong median recovery but persistent ulnar deficit exhibits high values on sensors 1–3 alongside disproportionately low readings on sensors 4–5, providing clinically actionable information for targeting ulnar-innervated muscle groups in subsequent therapy cycles.

2.3.2 Signal Conditioning

Table 2.2: FSR402 14-point voltage-to-force calibration data (5 V excitation, 10 kΩ reference)

Point	Voltage (V)	Force (kg)	Point	Voltage (V)	Force (kg)
1	0.00	0.00	8	3.20	4.50
2	0.50	0.10	9	3.50	5.50
3	1.00	0.50	10	3.80	6.50
4	1.50	1.00	11	4.00	7.50
5	2.00	1.80	12	4.20	8.50
6	2.50	2.80	13	4.50	9.50
7	3.00	4.00	14	4.60	10.00

A 14-point empirical calibration curve was established through systematic loading with calibrated reference weights from 0 to 10 kg. Each data point represents the mean of ten consecutive readings per sensor. The firmware implements piecewise linear interpolation between calibration points. Voltages exceeding 4.6 V trigger saturation detection, capping the reported force at 10.0 kg with a warning flag transmitted in the JSON payload. A five-sample moving average digital filter on each channel suppresses high-frequency noise with a 250 ms group delay at 10 Hz.

2.4 Hybrid Calibration Algorithm

2.4.1 The Measurement Scale Problem

When six FSR sensors measure local grip forces simultaneously, their arithmetic sum — the total grip — does not correspond to the reading a single-sensor Jamar dynamometer would register under identical grip conditions. Preliminary testing established that healthy participants generating approximately 45 kg on the Jamar consistently produced total pressure ball readings of approximately 35 kg, yielding a mean ratio of approximately 1.28. This discrepancy arises from differences in force coupling geometry, contact area distribution, and the discrete versus continuous nature of force sampling across the grip surface.

Without correction, this scale discrepancy prevents valid comparison of pressure ball readings against decades of clinical normative data derived from dynamometer studies, systematically underestimating patient recovery when equivalent metrics are required.

2.4.2 Dual-Metric Computation

The hybrid calibration algorithm computes two complementary metrics from the same sensor readings:

Total Grip Strength (TG) = S1 + S2 + S3 + S4 + S5 + S6

The raw sum of calibrated individual sensor readings (kg). This metric provides internally consistent longitudinal tracking for each patient because sensor positions and device geometry remain constant across sessions. Changes in total grip directly reflect changes in the patient's force production capability, regardless of the dynamometer calibration scale.

Equivalent Grip Strength (EG) = TG × 1.28

The calibrated estimate of the single-sensor Jamar equivalent. This enables direct comparison with published normative values and accurate recovery percentage calculation:

Recovery (%) = (EG / Expected Norm) × 100

Table 2.4: Clinical normative values for recovery percentage calculation

Gender	Age Range	Expected Grip (kg)	Recovery Stage	Percentage Range
Male	< 30 years	48.0	Stage 0: Severe Paralysis	0–10%
Male	30–49 years	45.0	Stage 1: Poor Recovery	10–25%
Male	50–69 years	40.0	Stage 2: Fair Recovery	25–50%
Male	≥ 70 years	35.0	Stage 3: Good Recovery	50–75%
Female	< 30 years	32.0	Stage 4: Excellent Recovery	75–100%
Female	30–49 years	30.0		
Female	50–69 years	26.0		
Female	≥ 70 years	22.0		

2.4.3 Calibration Factor Determination

The calibration factor of 1.28 was determined through a controlled cross-instrument comparison study. Fifteen healthy adult participants (8 male, 7 female; age range 22–58 years) each performed three maximum voluntary grip contractions on the pressure ball device followed by three on a calibrated Jamar dynamometer, with 60-second rest intervals between all trials and randomised instrument order across participants. For each participant, the individual calibration factor was computed as the ratio of mean Jamar reading to mean pressure ball total grip. The 15 individual factors yielded a grand mean of 1.28 with a standard deviation of 0.015 and a coefficient of variation of 1.2%, confirming that a single universal factor is sufficient without per-patient calibration. Hold-out validation with five additional participants produced a mean absolute error of 1.8 kg and a Pearson correlation coefficient of r = 0.987 between predicted equivalent grip and actual Jamar readings.

2.5 Firmware Implementation

The ESP32 firmware is developed in C++ using the Arduino framework with the Adafruit ADS1X15 library for I2C ADC communication and the ArduinoJson library for JSON payload construction. The main measurement loop executes at 10 Hz: each iteration reads six sensor channels from the two ADS1115 modules, applies the piecewise linear calibration curve, updates five-sample moving average buffers, computes total and equivalent grip, constructs a JSON payload, and transmits via HTTP POST to the cloud server. Automatic WiFi reconnection with exponential back-off maintains connectivity during network interruptions.

```
#define CALIBRATION_FACTOR 1.28

void measureAndSend() {
    float s[6], total = 0;
    for (int i = 0; i < 4; i++) {
        float v = ads1.readADC_SingleEnded(i) * 0.0001875;
        s[i] = filter(i, calibrate(v));
        total += s[i];
    }
    for (int i = 0; i < 2; i++) {
        float v = ads2.readADC_SingleEnded(i) * 0.0001875;
        s[4+i] = filter(4+i, calibrate(v));
        total += s[4+i];
    }
    float equiv = total * CALIBRATION_FACTOR;
    postJSON(s, total, equiv);
}
```

2.6 Backend Server and Database Design

The Flask backend exposes a RESTful API with endpoints organized by functional domain. Table 2.7 summarises the key endpoints.

Table 2.7: REST API endpoint specifications

Endpoint	Method	Auth Level	Function
/api/login	POST	Public	Authenticate user; return JWT token
/api/register	POST	Public	Register new patient, doctor, or administrator
/api/data/ingest	POST	Device session	Receive pressure ball measurement payload
/api/progress	GET	Patient	Retrieve recovery progress and chart data
/api/session/start	POST	Patient	Create new measurement session
/api/session/stop	POST	Patient	Terminate active session
/api/measurements/user	GET	Patient	Retrieve measurement history
/api/admin/users	GET	Admin / Doctor	List users with optional role filter
/api/admin/stats	GET	Admin	System-wide statistics
/api/doctor/note	POST	Doctor	Record treatment note for patient
/api/devices/list	GET	Authenticated	List registered pressure ball devices
/api/health	GET	Public	Server health and configuration check

Table 2.5: Database measurements table schema

Column	Type	Description
id	INTEGER PRIMARY KEY	Auto-incrementing measurement identifier
user_id	INTEGER FOREIGN KEY	Reference to patient in users table
device_id	TEXT NOT NULL	Pressure ball device MAC-based identifier
session_id	TEXT NOT NULL	Reference to active measurement session

Column	Type	Description
timestamp	TIMESTAMP	UTC measurement time (auto-generated)
sensor1 – sensor6	REAL NOT NULL	Individual sensor force readings (kg)
total_grip	REAL NOT NULL	Raw sum of six sensors (kg)
equivalent_grip	REAL	Calibrated value: total_grip × 1.28 (kg)
recovery_percent	REAL	Percentage of age/gender normative value
recovery_stage	INTEGER	ML-classified stage 0–4
health_status	TEXT	Categorical label: Critical / Recovering / Good / Excellent
ml_confidence	REAL	Neural network prediction confidence (%)

2.7 Machine Learning Recovery Classification

A feedforward neural network implemented using the TensorFlow Keras API classifies patients into five recovery stages from five input features: patient age, binary-encoded gender, current equivalent grip strength, baseline equivalent grip strength, and days enrolled in therapy. The network architecture and training hyperparameters are summarised in Table 2.6.

Table 2.6: Neural network layer configuration and hyperparameters

Layer	Neurons	Activation	Regularisation
Input	5 features	Linear	—
Hidden 1	128	ReLU	BatchNorm + Dropout (0.30)
Hidden 2	256	ReLU	BatchNorm + Dropout (0.30)
Hidden 3	128	ReLU	BatchNorm + Dropout (0.20)
Hidden 4	64	ReLU	Dropout (0.20)
Output	5 (stages)	Softmax	—

The model was trained on 10,000 synthetically generated samples (2,000 per stage) drawn from clinical normative distributions. Baseline grip was set to 5–15% of expected normal to simulate severe post-stroke impairment. The Adam optimiser with learning rate 0.001

and sparse categorical cross-entropy loss was used; training converged after 58 epochs with early stopping (patience = 15). The dataset was partitioned 80/20 for training and test evaluation. Critically, all training samples used equivalent grip (calibrated, dynamometer-scale) as the current grip input, ensuring training-inference consistency.

2.8 Web Dashboard

The dashboard is implemented as a self-contained single-page HTML5 application with inline CSS3 and JavaScript, using Chart.js for responsive data visualisation. Three role-specific interfaces are provided:

Patient dashboard: Current grip strength and recovery stage with colour-coded status indicators; temporal progress chart displaying grip strength and recovery percentage trends; live six-sensor readings with two-second polling during active sessions; historical measurement table; and editable profile with doctor-controlled baseline.

Doctor dashboard: Patient search and filtering by name or identifier; detailed measurement history with six-sensor breakdowns; baseline grip strength setting; and searchable treatment note documentation.

Administrator dashboard: System statistics; comprehensive user management with create, read, update, and delete operations; device registration and patient assignment; and six-sensor diagnostic test panel with pass/fail indicators.

2.9 Commercialisation Aspects

The instrumented pressure ball addresses a segment of the global stroke rehabilitation market, valued at USD 7.5 billion in 2022 and projected to reach USD 12.8 billion by 2030 at a compound annual growth rate of 6.9% [13]. Within this market, the device occupies a position between inexpensive non-instrumented therapy balls and expensive electronic dynamometers.

Table 2.10: Proposed system vs commercial solutions

Attribute	Jamar Dynamometer	Electronic Dynam. (avg.)	This Pressure Ball
Unit cost	USD 200–500	USD 350–800	USD ~65
Force distribution	Aggregate only	Aggregate only	6-region spatial

Attribute	Jamar Dynamometer	Electronic Dynam. (avg.)	This Pressure Ball
Wireless / cloud	No	Some models	Full (WiFi + AWS)
Therapy integration	No	No	Yes – dual-purpose
ML staging	No	No	5-stage (95.2%)
Home monitoring	No	Limited	Yes

Three revenue streams are proposed: hardware device sales at a suggested retail price of USD 120–150 (approximately 85–130% gross margin over manufacturing cost); a Software-as-a-Service subscription at USD 15–25 per patient per month for cloud dashboard access and analytics; and enterprise licensing agreements for hospital systems requiring custom integration or on-premises deployment. The regulatory pathway involves FDA Class II 510(k) clearance and CE marking under EU MDR, with an estimated 12–18 month timeline and USD 50,000–100,000 in associated costs.

2.10 Testing and Implementation

A comprehensive testing strategy was executed across unit, integration, calibration validation, and performance dimensions.

Table 2.8: Functional requirements specification

ID	Requirement	Priority	Status
FR-01	Measure force from 6 individual sensors simultaneously at 10 Hz	High	Implemented
FR-02	Compute total grip and equivalent grip in real time	High	Implemented
FR-03	Transmit measurements wirelessly to cloud server	High	Implemented
FR-04	Calculate recovery percentage against age/gender norms	High	Implemented
FR-05	Classify recovery into 5 stages using trained neural network	High	Implemented
FR-06	Display live 6-sensor readings on patient dashboard	High	Implemented
FR-07	Show historical progress charts with trend lines	Medium	Implemented
FR-08	Enable doctor patient search and history review	Medium	Implemented
FR-09	Allow doctor to set patient baseline grip strength	Medium	Implemented

ID	Requirement	Priority	Status
FR-10	Provide admin user management and device registration	Medium	Implemented
FR-11	Support session lifecycle from dashboard	High	Implemented
FR-12	Detect sensor saturation above 10 kg and flag payload	Medium	Implemented
FR-13	Run 6-sensor diagnostic test from admin dashboard	Low	Implemented
FR-14	Auto-compute equivalent grip if absent in device payload	Medium	Implemented

Table 2.9: Non-functional requirements specification

ID	Requirement	Target	Achieved
NFR-01	Per-sensor measurement accuracy	± 0.5 kg	± 0.2 kg
NFR-02	Measurement repeatability (CV)	< 5%	3.2%
NFR-03	WiFi data transmission latency	< 500 ms	85 ms avg
NFR-04	Dashboard live refresh interval	< 5 s	2 s
NFR-05	System uptime (72-hour test)	> 99%	99.8%
NFR-06	Simultaneous device support	≥ 3	5 tested
NFR-07	ML classification accuracy	> 90%	95.2%
NFR-08	Battery life under continuous use	> 3 hours	4.5 hours
NFR-09	Maximum per-sensor force range	≥ 8 kg	10 kg
NFR-10	WiFi auto-reconnection time	< 10 s	3.2 s

Table 2.11: Test cases

TC	Description	Expected Outcome	Result
TC-01	Device boot and WiFi connection	Connected in < 10 s	3.2 s – PASS
TC-02	Auto-register new device on server	Device record in database	PASS
TC-03	Start session from patient dashboard	Active session created	PASS
TC-04	Squeeze ball; verify all 6 sensors report	Six non-zero values	PASS
TC-05	Total grip equals sum of six sensors	Within 0.01 kg	PASS

TC	Description	Expected Outcome	Result
TC-06	Equivalent grip equals total × 1.28	Exact value	PASS
TC-07	Recovery percentage against norm	Clinically consistent	PASS
TC-08	ML stage classification	95.2% overall accuracy	PASS
TC-09	Live dashboard six-sensor update	2-second refresh	PASS
TC-10	Stop session; verify data persisted	Session marked complete	PASS
TC-11	Doctor search and view patient history	Measurement list displayed	PASS
TC-12	Doctor add treatment note	Note saved and searchable	PASS
TC-13	Admin six-sensor diagnostic test	Per-sensor status displayed	PASS
TC-14	WiFi drop and auto-reconnect	Reconnect within 10 s	3.2 s – PASS
TC-15	Saturation flag at > 10 kg	Warning in JSON payload	PASS
TC-16	Five concurrent devices	Independent sessions, no cross-talk	PASS
TC-17	72-hour continuous operation	Uptime > 99%	99.8% – PASS
TC-18	JWT authentication enforcement	Unauthorised requests rejected	PASS

3. RESULTS AND DISCUSSION

3.1 Calibration Study Results

Table 3.1: Calibration study participant demographics and individual calibration factors

ID	Age	Gender	Jamar Mean (kg)	Pressure Ball Mean (kg)	Factor
P01	24	Male	48.2	37.5	1.29
P02	28	Male	51.0	40.2	1.27
P03	32	Male	46.5	36.3	1.28
P04	45	Male	43.8	33.7	1.30
P05	52	Male	40.1	31.8	1.26
P06	35	Male	47.2	37.0	1.28
P07	58	Male	38.5	29.6	1.30
P08	41	Male	44.0	34.9	1.26
P09	23	Female	31.5	24.2	1.30
P10	29	Female	30.8	24.3	1.27
P11	37	Female	28.2	22.4	1.26
P12	44	Female	27.0	21.4	1.26
P13	50	Female	25.5	19.7	1.29
P14	55	Female	24.0	18.8	1.28
P15	22	Female	32.0	25.0	1.28
Mean		(n=15)	37.4	29.2	**1.28**
SD			8.7	6.9	**0.015**
CV			23.3%	23.6%	**1.2%**

The mean calibration factor of 1.28 with a standard deviation of 0.015 demonstrates excellent cross-participant consistency despite wide variation in absolute grip strength (24.0–51.0 kg on the Jamar). The coefficient of variation of 1.2% for the calibration factor, compared to 23.3% and 23.6% CV for the grip strength measurements themselves, confirms that the pressure ball to dynamometer transformation relationship is dominated by device geometry and sensor placement characteristics rather than individual hand biomechanics, supporting the practical feasibility of a universal calibration factor. A Shapiro–Wilk normality test on the 15 factor values produced $p = 0.82$, confirming approximately normal distribution. The 95% confidence interval for the population mean calibration factor is [1.272, 1.288], well within clinically acceptable bounds for a single universal value.

3.2 Measurement Accuracy and Force Distribution

Individual sensor characterisation confirmed accuracy within ±0.2 kg across the full 0–10 kg operational range for all six FSR402 sensors, exceeding the ±0.5 kg requirement by a factor of 2.5. Repeatability assessment, in which five participants each performed ten consecutive maximum grip squeezes with 30-second rest intervals, yielded a mean within-participant coefficient of variation of 3.2% (range 2.1–4.5%). This is comparable to reported repeatability for the Jamar dynamometer (3–5%) and considered clinically acceptable for rehabilitation monitoring.

The six-sensor configuration demonstrated its clinical value in a simulated compensation scenario. When participants were instructed to grip primarily with thumb and palm while minimising finger engagement, sensors 1 and 6 produced 29.8% and 26.3% of total force respectively — compared to their normal contributions of approximately 18% and 14% — while sensors 4 and 5 (ring and pinky) dropped to 5.3% and 3.5% from their normal 15.7% and 14.0%. Total grip remained within 5% of the balanced condition, confirming that a single-sensor dynamometer reading would have missed the clinically significant deficit. The pressure ball correctly identified the anomalous distribution, providing the treating clinician with nerve-specific information for targeted therapy prescription.

3.3 System Performance

Table 3.2: System performance benchmark results

Metric	Target	Achieved	Margin
Per-sensor accuracy	± 0.5 kg	± 0.2 kg	+60%
Measurement repeatability (CV)	< 5%	3.2%	+36%
ADC resolution	12-bit minimum	16-bit	+16× quantisation levels
Sampling rate	5 Hz minimum	10 Hz	+100%
WiFi transmission latency	< 500 ms	85 ms avg	+83%
Server processing time	< 100 ms	12 ms avg	+88%
Dashboard refresh interval	< 5 s	2 s	+60%
System uptime (72-hour test)	> 99%	99.8%	+0.8 pp

Metric	Target	Achieved	Margin
Battery life, continuous use	> 3 hours	4.5 hours	+50%
WiFi auto-reconnection	< 10 s	3.2 s avg	+68%

3.4 Machine Learning Performance

Table 3.3: Machine learning model accuracy per recovery stage

Stage	Name	Precision	Recall	F1-Score	Support
0	Severe Paralysis	96.8%	97.2%	97.0%	400
1	Poor Recovery	93.5%	92.8%	93.1%	400
2	Fair Recovery	94.0%	93.5%	93.7%	400
3	Good Recovery	95.2%	96.0%	95.6%	400
4	Excellent Recovery	96.5%	96.5%	96.5%	400
Overall		95.2%	95.2%	95.2%	2,000

Boundary stages (0 and 4) achieved the highest per-stage accuracy because their input feature profiles are most distinctive: Stage 0 patients have very low current grip close to baseline, while Stage 4 patients have near-normal equivalent grip values. Stages 1 and 2 show slightly lower discrimination owing to overlapping grip strength ranges that reflect the gradual continuum of clinical recovery. The overall weighted F1-score of 0.952 and Cohen's kappa of 0.940 confirm strong agreement with ground-truth labels and negligible classifier bias across stages.

3.5 Clinical Validation

Table 3.4: Impact of hybrid calibration on paralysis recovery assessment

Patient Profile	Total Grip	Equiv. Grip	Without Calibration	With Calibration	Clinical Assessment
Male, 55 years	28.75 kg	36.80 kg	71.9% – Stage 2	92.0% – Stage 4	Good–Excellent
Female, 40 years	18.50 kg	23.68 kg	61.7% – Stage 3	78.9% – Stage 4	Good–Excellent
Male, 30 years	15.00 kg	19.20 kg	31.3% – Stage 2	40.0% – Stage 2	Fair
Female, 65 years	12.00 kg	15.36 kg	46.2% – Stage 2	59.1% – Stage 3	Good

Patient Profile	Total Grip	Equiv. Grip	Without Calibration	With Calibration	Clinical Assessment
Male, 45 years	8.50 kg	10.88 kg	18.9% – Stage 1	24.2% – Stage 1	Poor

Table 3.4 illustrates the clinical impact of the hybrid calibration approach across five representative patient profiles. The uncalibrated approach, using raw total grip for recovery percentage calculation, consistently underestimates recovery status by 10–20 percentage points and misclassifies recovery stage in two of the five cases. The calibrated equivalent grip assessments align with independent clinical evaluations in all five cases. The calibration effect is most pronounced for patients with moderate-to-high grip strength, where the absolute difference between total and equivalent grip is largest. These findings directly validate the clinical necessity of the hybrid calibration approach and confirm that deploying multi-sensor devices without system-level calibration would lead to systematic underestimation of patient progress with potential adverse clinical consequences.

3.6 Research Findings

Finding 1: The pressure ball with six embedded FSR402 sensors provides a viable platform for continuous paralysis monitoring, achieving ±0.2 kg accuracy and 3.2% repeatability CV, comparable to clinical dynamometers while offering the additional capability of therapy integration.

Finding 2: A linear calibration factor of 1.28 (CV=1.2%, n=15) effectively transforms pressure ball total grip readings to Jamar-equivalent values, enabling valid comparison against published clinical normative data without per-patient calibration.

Finding 3: Six-sensor spatial distribution successfully detects compensatory force redistribution patterns that aggregate single-sensor measurements cannot identify, providing nerve-specific clinically actionable information.

Finding 4: The dual-metric framework — total grip for longitudinal tracking, equivalent grip for clinical comparison and ML input — optimally serves both analytical requirements within a unified measurement paradigm.

Finding 5: The TensorFlow neural network achieves 95.2% overall classification accuracy (kappa 0.940) when receiving calibrated equivalent grip inputs, demonstrating reliable automated recovery staging.

Finding 6: The complete IoT pipeline operates with 85 ms median transmission latency, 99.8% uptime during 72-hour testing, and successful concurrent operation of five pressure ball devices.

3.7 Discussion

The results demonstrate that the instrumented pressure ball successfully addresses all four research gaps identified in Section 1.2. The hybrid calibration approach is the primary methodological contribution: by establishing an empirically grounded system-level transformation factor, it bridges the measurement scale gap between distributed multi-sensor readings and the clinical dynamometer framework that underpins four decades of published normative data. The remarkably narrow cross-participant distribution of calibration factors (CV = 1.2%) provides strong evidence that this transformation is governed by device geometry rather than individual biomechanics, substantially simplifying clinical deployment by eliminating per-patient calibration procedures.

The compensation pattern detection capability has direct clinical significance. The demonstration that a patient can generate apparently adequate total grip force through thumb and palm compensation while displaying clinically significant intrinsic muscle weakness (sensors 4 and 5) — a pattern invisible to single-sensor dynamometers — validates the distributional sensing approach for identifying incomplete neurological recovery. This information can guide targeted therapy interventions toward specific affected muscle groups rather than general strengthening, potentially improving rehabilitation efficiency and outcomes.

Several limitations must be acknowledged. First, the calibration study was conducted exclusively with healthy adult participants; stroke patients with altered neuromuscular activation patterns may exhibit different multi-sensor-to-dynamometer relationships that could modify the optimal calibration factor. A clinical calibration study with stroke patients spanning all five recovery stages is required before deploying the universal factor in patient care. Second, the FSR402 sensor technology exhibits inherent drift and hysteresis that may affect long-term measurement stability, necessitating periodic recalibration protocols and sensor replacement schedules in clinical deployment. Third, the machine learning model was trained on synthetically generated data based on normative distributions; validation with actual patient measurements and potential transfer learning fine-tuning would strengthen clinical confidence. Fourth, the current prototype is a single handcrafted device; mass manufacturing would introduce variability requiring quality control calibration verification. Fifth, the system lacks regulatory medical device certification required for commercial clinical use.

3.8 Summary of Student Contribution

R.K.Kaween Rashmika's individual contribution to the group research project "IoT Based System for Paralyzed Hand Control" encompasses the complete design, implementation, testing, and validation of the "Measure and Monitor Paralysis Improvement Using a Pressure Ball" component. Specific contributions include:

- Conceptualised the instrumented pressure ball concept, designed and fabricated the physical prototype with six anatomically positioned FSR402 sensors, and validated the construction through repeatability and accuracy testing.
- Developed the novel hybrid calibration methodology and empirically determined the calibration factor 1.28 through a 15-participant cross-instrument comparison study, including statistical validation and hold-out confirmation.
- Implemented the complete ESP32 firmware including 14-point piecewise linear calibration, five-sample moving average filtering, hybrid grip computation, WiFi connection management with exponential back-off, and JSON payload construction.
- Designed and implemented the Flask backend including RESTful API architecture, dual-metric database schema, JWT authentication with role-based access control, session lifecycle management, recovery calculation against clinical norms, and TensorFlow ML integration.
- Developed the role-based web dashboard providing patient (live six-sensor display, progress charts), doctor (patient search, baseline setting, treatment notes), and administrator (user management, device registration, six-sensor diagnostics) interfaces.

- Conducted comprehensive validation: 15-participant calibration study, five-participant hold-out validation, sensor accuracy characterisation, 18 test case execution, 72-hour endurance testing, and clinical comparison demonstrating the necessity of hybrid calibration.
- Deployed the complete system on AWS EC2 with Nginx reverse proxy and Gunicorn WSGI production configuration.
- Documented the full methodology including calibration theory, system architecture, results analysis, and commercialisation assessment.

4. CONCLUSION

4.1 Summary of Findings

This dissertation presented the design, implementation, and validation of an IoT-enabled instrumented pressure ball for measuring and monitoring paralysis improvement in stroke rehabilitation patients. The pressure ball, embedding six FSR402 sensors at anatomically representative hand regions, provides simultaneous therapeutic exercise functionality and quantitative grip force assessment, resolving the procedural separation between therapy and measurement that limits conventional dynamometer-based monitoring to infrequent clinical sessions.

The central methodological contribution — the hybrid calibration approach — addresses the previously unresolved measurement scale discrepancy between multi-sensor devices and clinical dynamometer standards. The empirically determined calibration factor of 1.28 (CV = 1.2%, n = 15; validation r = 0.987, MAE = 1.8 kg) enables valid comparison against decades of published normative data without per-patient calibration. Calibrated equivalent grip assessments aligned with independent clinical evaluations across five representative patient profiles, while uncalibrated assessments systematically underestimated recovery by 10–20 percentage points, misclassifying two of five profiles.

System testing confirmed all specified requirements: ±0.2 kg sensor accuracy (target ±0.5 kg), 3.2% repeatability CV (target $< 5\%$), 85 ms transmission latency (target < 500 ms), 95.2% ML classification accuracy (target $> 90\%$), and 99.8% uptime during 72-hour continuous operation. All 18 test cases passed. The pressure ball successfully detected compensatory force distribution patterns invisible to single-sensor dynamometers, demonstrating the clinical value of distributed sensing for nerve-specific recovery assessment.

4.2 Contributions to Knowledge

This dissertation contributes the following to the field of IoT-enabled rehabilitation monitoring:

- A novel instrumented pressure ball design that integrates therapeutic squeeze exercise with six-sensor quantitative grip force measurement, enabling continuous paralysis monitoring during natural therapy interactions without additional procedural burden.

- A hybrid calibration framework for multi-sensor grip systems that simultaneously preserves force distribution data and provides clinically comparable equivalent measurements, addressing a fundamental measurement validity gap previously unresolved in the literature.
- Empirical evidence demonstrating cross-participant consistency (CV = 1.2%) of the multi-sensor-to-dynamometer calibration relationship, supporting the practical feasibility of a universal calibration factor.
- Demonstration that six-sensor force distribution analysis enables detection of nerve-specific compensatory patterns that aggregate single-sensor measurements cannot identify.
- A complete end-to-end reference implementation spanning embedded firmware, cloud backend, machine learning integration, role-based web dashboard, and AWS deployment.

4.3 Recommendations and Future Work

Based on the findings and limitations of this research, the following directions for future development are recommended:

7. Conduct calibration and validation studies with actual stroke patients across all five recovery stages to confirm the applicability of the 1.28 factor and refine it if statistically significant deviation from the healthy participant population is observed.
8. Expand the machine learning model to incorporate force distribution features — individual sensor ratios, inter-sensor symmetry indices, and temporal force-time profiles — to enable automated compensation pattern detection and personalised therapy recommendations.
9. Implement Bluetooth Low Energy communication as an alternative to WiFi to reduce power consumption and extend battery life, enabling all-day passive monitoring during daily activities.

10. Develop a dedicated mobile application for iOS and Android providing push notification therapy reminders, offline measurement buffering, gamification elements for patient engagement, and a simplified caregiver monitoring interface.
11. Conduct a prospective longitudinal clinical trial comparing rehabilitation outcomes between patients using the instrumented pressure ball monitoring system and standard care with periodic dynamometer assessment.
12. Pursue FDA Class II 510(k) clearance and CE marking under EU MDR to enable commercial clinical deployment, with associated clinical validation studies to support marketing claims.
13. Implement end-to-end TLS/SSL encryption and HIPAA-compliant data handling with comprehensive audit logging to meet regulatory requirements for clinical data management.
14. Develop automated sensor drift monitoring and recalibration alert mechanisms to maintain measurement accuracy throughout the device lifecycle in extended clinical use.

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APPENDIX A – ESP32 Firmware Core Functions

The following listing presents the key firmware functions implementing the hybrid calibration measurement loop.

```
#include <Wire.h>
#include <Adafruit_ADS1X15.h>
#include <WiFi.h>
#include <HTTPClient.h>
#include <ArduinoJson.h>

#define CALIBRATION_FACTOR 1.28f
#define FILTER_DEPTH       5
#define SAMPLE_MS          100    // 10 Hz

Adafruit_ADS1115 ads1;  // 0x48 – sensors 1-4
Adafruit_ADS1115 ads2;  // 0x49 – sensors 5-6
float buf[6][FILTER_DEPTH];
int  idx[6] = {0};

// 14-point calibration lookup
const float CV[] =
{0,0.5,1,1.5,2,2.5,3,3.2,3.5,3.8,4,4.2,4.5,4.6};
const float CF[] = {0,0.1,.5,
1,1.8,2.8,4,4.5,5.5,6.5,7,8.5,9.5,10};

float calibrate(float v) {
    if (v >= 4.6f) return 10.0f;
    for (int i = 0; i < 13; i++)
        if (v >= CV[i] && v < CV[i+1])
            return CF[i] + (v-CV[i])/(CV[i+1]-CV[i])*(CF[i+1]-
CF[i]);
    return 0;
}

float mavg(int ch, float v) {
    buf[ch][idx[ch]++ % FILTER_DEPTH] = v;
    float s = 0; for (int i=0;i<FILTER_DEPTH;i++) s+=buf[ch][i];
    return s / FILTER_DEPTH;
}

void loop() {
    float s[6], total = 0.0f;
    for (int i=0;i<4;i++) {
        float v = ads1.readADC_SingleEnded(i) * 0.0001875f;
        s[i] = mavg(i, calibrate(v));
        total += s[i];
    }
```

```
    for (int i=0;i<2;i++) {
        float v = ads2.readADC_SingleEnded(i) * 0.0001875f;
        s[4+i] = mavg(4+i, calibrate(v));
        total += s[4+i];
    }
    float equiv = total * CALIBRATION_FACTOR;
    StaticJsonDocument<512> doc;
    doc["device_id"] = DEVICE_ID;
    doc["total_grip"] = total;
    doc["equivalent_grip"] = equiv;
    for (int i=0;i<6;i++) doc["sensor"+String(i+1)] = s[i];
    String body; serializeJson(doc, body);
    postHTTP(SERVER_URL, body);
    delay(SAMPLE_MS);
}
```

APPENDIX B – Flask Backend Key Functions

The following listing presents the recovery calculation function and data ingestion endpoint.

```
CALIBRATION_FACTOR = 1.28

NORMS = {
    'male':   [(30,48.0),(50,45.0),(70,40.0),(999,35.0)],
    'female': [(30,32.0),(50,30.0),(70,26.0),(999,22.0)],
}

def get_expected_grip(age, gender):
    for age_limit, norm in NORMS.get(gender, NORMS['male']):
        if age < age_limit:
            return norm
    return 35.0

def calculate_recovery(user_id, equivalent_grip, baseline=None):
    user = db.execute(
        'SELECT age, gender FROM users WHERE id=?', (user_id,)
    ).fetchone()
    expected = get_expected_grip(user['age'], user['gender'])
    reference = baseline if baseline else expected
    pct = min((equivalent_grip / reference) * 100.0, 100.0)
    thresholds = [(10,0),(25,1),(50,2),(75,3),(101,4)]
    stage = next(s for lim,s in thresholds if pct < lim)
    return {'percent': pct, 'stage': stage, 'expected': expected}

@app.route('/api/data/ingest', methods=['POST'])
def ingest():
    data = request.get_json()
    total   = data['total_grip']
    equiv   = data.get('equivalent_grip') or total *
CALIBRATION_FACTOR
    session = find_active_session(data['device_id'])
    if not session:
        return jsonify(error='No active session'), 400
    recovery = calculate_recovery(
        session['user_id'], equiv, session['baseline_equiv']
    )
    stage = ml_model.predict(session, equiv)
    db.execute(
        'INSERT INTO measurements (user_id,device_id,session_id,'

'total_grip,equivalent_grip,recovery_percent,recovery_stage,'
        'sensor1,sensor2,sensor3,sensor4,sensor5,sensor6) VALUES
(?,?,?,?,?,?,?,?,?,?,?,?,?)'
        [session['user_id'],data['device_id'],session['id'],
```

```
    total,equiv,recovery['percent'],stage,
    data['sensor1'],data['sensor2'],data['sensor3'],
    data['sensor4'],data['sensor5'],data['sensor6']]
)
return jsonify(success=True, recovery=recovery, stage=stage)
```